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THE EFFECT OF PROCESS DIGITALIZATION INITIATIVE ON FIRM PERFORMANCE: A DYNAMIC CAPABILITY DEVELOPMENT PERSPECTIVE

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The effect of process digitalization initiative on firm performance: A dynamic capability development perspective

Abstract

Digitalization has been increasingly adopted to transform the manufacturing process and considered as effective to achieve product customization, process efficiency, and firm performance for companies. Nevertheless, misalignment among digital initiative and existing operational routines are found in some companies, making the effectiveness of process digitalization initiative (PDI) uncertain. This research empirically investigates the effect of PDI on firm performance. Taking the perspective of dynamic operational capability, this study considers three key organizational factors, i.e., differentiation strategy, absorptive capability and lean production mechanism, that can facilitate firms to align their existing operational processes with digital technology and examine how they affect the implementation of PDI. We employ the long-horizon event study approach using the panel data collected from 168 firms adopting PDI in China during the period between 2006 and 2018. The differential findings of this study demonstrate that PDI implementation enhances firm performance. The results also show that differentiation strategy and absorptive capacity can enhance the effect of PDI implementation, but lean production has a substitution role in the effect of PDI. This research contributes to the literature on digital transformation and dynamic capability by investigating the actual effects of PDI implementation and exploring the key elements for its success from a novel perspective (i.e., dynamic capability development). This research also provides practical guidelines to enterprises how to conduct effective process digitalization and valuable insights to governments how to support enterprises for digitalization.

KEYWORDS: process digitalization initiative; dynamic operational capability; differentiation strategy; absorptive capacity; lean production mechanism

1. INTRODUCTION

With the rapid development of information and communication technology, digitalization is an imperative driver of innovation in many industrial sectors, such as the automobile industry and the electronic industry (Schneider, 2018). In industrial sectors, digitalization is commonly adopted to transform manufacturing process in companies, for example, General Electric, Timberland and Tasly (D'Aveni, 2015; Accenture and China Industrial Control Teams, 2018). Process digitalization initiative (PDI) is defined as the application of digital, intelligent and networking technologies (e.g., cloud-based technologies and additive manufacturing) to automatically handle data, optimize processes and conduct self-decision-making for production, thereby creating value and generating revenue for companies (Nambisan et al., 2017; Kache and Seuring, 2017; Chen et al. 2018; Koh et al., 2019; Branca et al., 2020; Lager and Chirumalla, 2020). More companies have adopted PDI; however, there is a concern about its performance contribution. It is reported that only 0.04% of global industrial outputs was achieved through digitalizing production processes (Forbes, 2018). An industrial report reveals that over 90% of the enterprises in China employing digital technologies in manufacturing failed to attain expected performance (Accenture and China Industrial Control Teams, 2018).

The current literature provides two different views concerning the role of PDI in firm performance. One view is that process digitalization is important to create business value since it can improve operational performance (e.g., inventory cost reduction and material usage reduction) and innovation performance (e.g., R&D efficiency and product customization) (e.g., Lam et al. 2019; Branca et al., 2020; Lager and Chirumalla, 2020). Another view considers that digital technology could induce operational and financial risks to companies because of the difficulty in aligning advanced technology with traditional operational routines (e.g., Kessler et al., 2022), making the performance of PDI implementation uncertain. Moreover, regardless the two views, the existing research on PDI is dominated by theoretical analysis and exploratory case studies, with limited empirical support for its performance (Li et al. 2020). Hence, there is a concern about the real performance of PDI implementation, leading to an urge for further investigation to empirically reveal the actual implementation performance of PDI.

To address the above-mentioned gap, this study aims to examine (1) whether the implementation of PDI affects firm performance and (2) how the implementation of PDI can be facilitated. Scholars have generally advocated that firms pursuing digital transformation should focus on acquisition, integration and reconfiguration of the internal and external resources in operational processes (e.g., Gürdür et al., 2019; Gao et al., 2019). In this regard, dynamic capability, which refers to a firm's "ability to integrate, build and reconfigure internal and external competences to address rapidly changing environments" (Teece et al., 1997, p. 516), is considered as essential to facilitate rapid diffusion of a firm's process digitalization initiative into a firm's operational routine (Heinen and Hoberg 2019; Roscoe et al., 2019). Accordingly, this study takes the dynamic operational capability perspective to understand PDI implementation and further explore some key factors that can leverage a firm's capability when implementing PDI.

The extant literature on dynamic capability generally considers that the development of capability depends on various factors, including organizational direction, strategy planning, process, procedures, skills, knowledge development and management as well as R&D activities, (Teece, 2007; Swink et al., 2007; Peng et al., 2008; Montgomery, 2008; Huang et al., 2008; Roscoe et al., 2019). Based on prior studies (e.g., Ghoshal et al., 1994; Anand et al., 2009), these factors are classified into three dimensions as the basis of dynamic capability development. They are: purpose (e.g., organizational direction and strategic planning), people capability (e.g., knowledge development and management) and process (e.g., procedures and routines). This research refers to these dimensions to identify three corresponding constructs (i.e., one construct for one dimension) that are necessary for the implementation of PDI. They are differentiation strategy, absorptive capability and lean production, that are identified for the dimensions of purpose, people capability and process, respectively, of the dynamic capability development.

First, a firm's purpose concerns with organizational direction, vision and objectives that are achieved by developing proper organizational strategy to guide daily activities and such strategy determines whether the firm can be flexible while coping with the changes in operational environments (Nelson and Winter, 1982; Anand et al., 2009). When the firm adopts the differentiation strategy, it is likely to be flexible in performing daily routines in production and customization in response to the changes of the operational environment, leading to developing more dynamic capability (Yi et al., 2016). Firm with differentiation strategy are therefore more able to scan, seize and manage digital manufacturing opportunities. Second, people capability relevant to knowledge development refers to the ability that employees absorb the internal and external knowledge of a company and integrate them to create new knowledge (Chen et al., 2018). The literature suggests that organizational absorptive capacity as an important knowledge development capability for an organization's operational unit to obtain, assimilate and exploit new knowledge from external sources (Tu et al., 2006; Patel et al., 2012). It guides companies to diffuse digital technology into the existing routine in production while achieving digital manufacturing. Last, operational process influences the ultimate outcome of dynamic capability deployment (Teece, 2007). In an operational system of manufacturing, lean production relies mainly on a firm's potential utilizable resources reconfiguration and combination to minimize the production cost and maximize the value delivered to customers (Chopra and Meindl, 2004; Rai et al., 2006). This implies that the reconfiguration ability and uniform methods of a company can facilitate the firm's dynamic capability deployment required for PDI implementation. Hence, this study intends to explore whether differentiation strategy, absorptive capacity and lean production can affect the effectiveness of process digitalization.

This study employs the approach of long-horizon event study using data collected from 168 firms implementing PDI in China. The findings of this study show that the implementation of PDI makes a positive impact on firm profitability. The results also demonstrate that stronger differentiation strategy and higher absorptive capability are key resources to develop dynamic operational capability that is beneficial to PDI implementation, whereas lean production could weaken the effect of PDI implementation on profitability (i.e., lean production has a substitute effect on the role of PDI). This study makes two major contributions. First, it takes longitudinal data to empirically examine the actual effect of process digitalization. The findings demonstrate the actual performance of PDI implementation and how the performance is improved. Second, it links dynamic capability with digital transformation to explore the situations that the role of PDI can be leveraged. The results emphasize the importance of strategic orientation and knowledge development capability and reveal that lean production has a substitution role in the PDI implementation process. This research also provides practical guidelines to enterprises how to conduct effective process digitalization and valuable insights to governments how to support enterprises for digitalization.

2. THEORETICAL BACKGROUND

2.1 Process digitalization initiative

Process digitalization integrates with advanced information technologies (e.g., digital sensory technology and cloud-based data storage) and manufacturing technologies (e.g., 3D printing) to obtain customer real-time data and derive products directly from 3D CAD model and manufacture them at or close to the customer end (Gibson et al, 2010). Given that PDI can effectively obtain timely customer demand, it helps firms make accurate decisions for product design and production, thereby increasing product popularity and decreasing new product trial cost and inventory cost (e.g., Atzeni and Salmi, 2012; Chen et al., 2015).

The studies investigating the effect of PDI is limited and their conclusions are mixed. Gibson et al. (2010) and Chen et al. (2015) indicate that digital innovation can improve material usage situation, shorten the entire supply chain cycle, reduce inventory and innovation risks and enhance customer satisfaction. Berman (2012) and Lam et al. (2019) demonstrate that 3D printing can achieve product customization, inventory cost reduction, R&D efficiency improvement and increased stock returns. However, some studies reveal that digital technology is not really helpful to achieve expected performance. Guha and Kumar (2018) and Wamba et al. (2015) show that digital technology increases operational cost and organizational resources waste, thereby diminishing a firm's financial performance. Kessler et al. (2022) find that the implementation of digital technology is accompanied by some severe risks in industrial operations, such as information asymmetries between digital technology developers and users for legal issues (e.g., data privacy and security). As can be seen, the current literature is unclear to reveal the actual impact of PDI on firm performance, requiring further investigation.

2.2 Dynamic capability development

Dynamic capability is generated from the resource-based view of a firm for developing competitive advantage (Barney et al., 2001). The development of dynamic capability depends on firms' key resources, for instance, strategic decisions, operational routines, skills, knowledge development and management as well as R&D activities (Teece, 2007; Swink et al., 2007; Peng et al., 2008; Montgomery, 2008; Huang et al., 2008; Roscoe et al., 2019). Anand et al. (2009) suggested three dimensions as the foundation of dynamic capability development. They are: purposes (e.g., organization direction and vision), people capability (e.g., knowledge development and management), process (e.g., procedures and routines). In this study, we followed these three dimensions to explore the key constructs that can facilitate the PDI implementation.

Specifically, for the first dimension, a firm's purpose refers to organizational vision and operations objectives, which are commonly reflected by strategic orientation. Firms' strategic direction allowing flexibility in response to changes in environments is critical for achieving dynamic capability (Anand et al., 2009). Differentiated strategic orientation could determine a firm's daily activities how to implement and resources how to allocate to routines; in turn, this influences the flexibility of performing operational activities and the firm's capability of coordinating its new and existing resources (Ostroff and Bowen, 2000; Yen et al., 2012). Therefore, strategic orientation is considered as the first key factor influencing PDI implementation by reflecting a firm's purpose. For the second dimension, knowledge development and management capacity refer to the ability of knowledge acquisition, creation and deployment (Peng et al., 2008, Liu et al., 2014). Relevant literature indicates that absorptive capacity is a key ability to acquire and create knowledge from various external information sources, thereby developing dynamic capability for the adaption of technological innovation (Daniel et al., 2004). Thus, in this study, absorptive capacity is regarded as the second key factor influencing PDI implementation by developing knowledge relevant capabilities. For the last dimension, dynamic capability deployment requires operational routines to support for resources configuration and combination as well as process innovation to achieve competitive advantage (Chen et al., 2018), which is consistent with the goal of a lean process that effectively and efficiently allocates organizational resources and improve process to achieve maximum value (Rathore et al., 2018; Iyer et al., 2019). Hence, lean production is regarded as a key factor influencing PDI implementation by providing a lean operational process with resources configuration. To sum, this study considers differentiation strategy, absorptive capacity and lean production as the key factors influencing PDI implementation from the dynamic capability development perspective.

3. HYPOTHESES DEVELOPMENT

To seek more understanding about the organizational performance generated from PDI implementation, we firstly examine how PDI makes an impact on a firm's performance and further explore how such impact is affected by the three key organizational factors, i.e., differentiation strategy, absorptive capability and lean production. Figure 1 shows the conceptual framework. In what follows, we describe how the hypotheses are developed.

(------ Figure 1 about here ------)

3.1 Process digitalization initiative and firm profitability

Given that digital technologies are perceived to reduce the operational cost and offer new and personalized products to meet customer requirements and achieve market share, firms increasingly adopt digitalization to cope with dynamic business environment (Judge et al., 2009). Process digitalization, one kind of digitalization, can effectively obtain timely and accurate data through a digital platform and reduce the consumption of energy and material by using digital production (e.g., activity-based costing methods) (Atzeni and Salmi, 2012). Moreover, when products are derived from a digital model without tooling and modeling setup and are manufactured close to customer end, production and transportation costs are reduced (Chen et al., 2015). Besides, research examining the effects of digital production technology show that the return of investment is higher in using digital production than in traditional manufacturing practices, due to reduced shipping cost and energy consumption (Wittbrodt et al., 2013). Thus, firms implementing PDI provides cost-effective solutions for manufacturing. This helps firms promptly and accurately learn about customers' requirements and preferences to engender multiple innovations in products, routine practices and knowledge, thereby attracting more customers and ultimately increasing the market share (Boland Jr et al., 2007; Mellor et al., 2014). Accordingly, we propose:

H1: Process digitalization initiative improves firm's profitability.

3.2 The moderating effect of differentiation strategy

Strategic orientation can reflect how and when daily operations are executed while achieving organizational goals (Nelson and Winter, 1982), which supports firms to pursue organizational goals and determine resources allocation and practices that keep with their competitive advantages (Ostroff and Bowen, 2000; Veld et al., 2010). Strategic contingencies can provide stable routinized operational blocks that are helpful to cultivate standardized problem-solving and reflection-review abilities as well as determine operational flexibility and efficiency

(Ostroff and Bowen, 2000; Veld et al., 2010). The literature on organizational strategic orientation describes two kinds of generic strategy, i.e., cost leadership and differentiation (Kim et al., 2004). Cost leadership strategy determines the organizational routines (e.g., resource allocation methods and manufacturing methods) that are required to take a low-cost position to increase market share (Banker et al., 2014); therefore, it enables firms to generate a cost-based manufacturing strategy (Ward and Duray, 2000). Differentiation strategy determines organizational routines that help offering unique service or product to meet individual customers' requirements (e.g., new product or service development investment) (Banker et al., 2014); hence, it facilitates firms to generate quality, flexibility and innovation-based manufacturing strategy (Ward and Duray, 2000).

The literature demonstrates that the competitive priority of cost-leadership strategy is based on cost, generating routines that are well-organized, controlled rigidly and lacked of flexibility (Devaraj et al., 2004; Das and Joshi, 2007; Felin et al., 2012), whereas differentiation strategy involves flexible processes that facilitate firms to propose creative idea and encourage them to perform innovative tasks, which is more relevant to operational objectives associated with continuous improvement and radical innovation (Devaraj et al., 2004; Felin et al., 2012). PDI emphasizes that firms need test and assimilate digital technologies through learning and problem-solving behaviors and conduct exploitative and explorative activities to acquire and accumulate knowledge for facilitating new process innovation (Hoopes and Madsen, 2008). Thus, cost leadership strategy tends to take a limited role in developing operational capabilities for PDI, whereas differentiation strategy is likely to be an important intangible condition for developing dynamic operational capabilities in digital manufacturing.

Firms with differentiation strategy are often capable of product customization, which requires a close relationship with customers and suppliers (Graham and Bansal, 2007). The close relationship can enhance the willingness to share knowledge among firms, customers and suppliers (Banker et al., 2014). Moreover, firms with differentiation strategy focus more on developing creative capability by conducting cross-functional cooperation and customer participation in product development to achieve sustainable competitive advantage (Coombs and Bierly, 2006). Under such an environment, PDI can be diffused into the existing production processes and systems more easily and rapidly. Firms with differentiation strategy also necessitates to develop close relationships among different supply chain participants (Banker et al., 2014). This assures that accurate and real data from customers and suppliers are used in digital manufacturing more effectively, thereby improving firm profitability. Therefore, the second hypothesis is:

H2: Differentiation strategy enhances the effectiveness of process digitalization initiative on firm profitability.

3.3 The moderating effect of absorptive capability

Based on the lens of dynamic capability, the literature has indicated that learning behavior facilitates knowledge creation and results in generating explicit and tacit knowledge that can be embedded in operational routines, thereby leading to develop mass customized capabilities (Huang et al., 2008). Many researchers have realized the importance of absorptive capacity in operational processes (e.g., Patel et al., 2012). It is considered as an important learning capability for an organization's operational units to obtain, assimilate and exploit knowledge from external sources and to link the knowledge with operational flexibility and uncertain operational environment (Tu et al., 2006; Patel et al., 2012). The literature relevant to innovation also proposes that the ability in combing the existing and new resources can prompt firms to create the knowledge required for developing adaptive capabilities (Yen et al., 2012). Absorptive capacity is therefore an essential factor for developing capabilities in process innovation.

Organizations adopting PDI have radical change in production process and operational measures (Chen et al., 2015). Such kind of radical change requires operational units to have dynamic capability to adapt the changes so as to facilitate the success of PDI implementation. Refer to absorptive capacity, it can acquire and assimilate relevant information from external resources as well as reconfigure and realign with internal resources to enhance knowledge creation and sharing in response to process innovation (Yam and Chan, 2015). Organizations with absorptive capacity are more proactively and effectively to acquire external information and knowledge to realign their elements in manufacturing, such as materials, labor and their product portfolios. This enables the development of dynamic capability for PDI. Further, evidences indicate that absorptive capability can enhance firms' capability of diffusing the manufacturing practices and innovation into organizations (Tu et al., 2006; Autry et al., 2010). Such learning capability can help firms rapidly assimilate the new change, which facilitates successful implementation of PDI. Thus, organizations with a high level of absorptive capacity are prone to acquire external information, integrate internal resources and assimilate new changes in order to cope with operational mode changes required in implementing PDI. We thus suggest:

H3: Absorptive capacity strengthens the effectiveness of process digitalization initiative on the firm's profitability.

3.4 The moderating effect of lean production

The literature concerning process innovation and digitalization advocates that firms need acquisition, integration and reconfiguration of the internal and external resources in operational processes (Gürdür et al., 2019; Gao et al., 2019). Lean production, comprised by a set of lean principles, leverages different resources and setup cost skills and designs for manufacturing in order to decrease excessive inventory and increase output rates (Prajogo et al., 2016). Moreover, such lean principles can reduce the variation and uncertainty in operational processes by standardizing and repeating the processes (Lockamy et al. 2008; Rathore et al., 2018). Further, lean principles provide mechanisms to cultivate firms' ability in configuring and combining knowledge and resources; in turn, this eliminates repetitive routines and waste, leading to the development of an efficient operations system (Reichart and Holweg 2007). The literature also shows that firms with lean production favor switching among various innovation strategies for the sake to attain continuous process improvement (Netland and Ferdows, 2016; Rathore et al., 2018). Lean production is therefore an element conducive to developing dynamic capability for PDI implementation.

We further argue that how lean production can facilitate PDI implementation. Firstly, lean production can reduce the variations and uncertainties that are arisen from supply and demand by standardized processes and efficient operational practices (Rathore et al., 2018). PDI employs digital technology to change existing operational routines and measures (Mellor et al., 2014), leading to increasing the uncertainty of internal process and supply. Firms with lean production can effectively cope with such uncertainty. Secondly, continuous improvement is the indispensable requirement of lean production which can impel firms' exploration and risk-taking for innovation (Netland and Ferdows, 2016). Therefore, lean firms are more likely to have risk propensity and seek novel attempts; in turn, they offer innovation environment and experience for process digitalization implementation. Finally, lean firms have strong abilities in acquisition, integration and reconfiguration of the internal and external resources, thereby enhancing the effect of PDI implementation. The last hypothesis is:

H4: Lean production strengthens the effectiveness of process digitalization initiative on firm profitability.

4. METHOD

4.1 Research setting

The sample of this study is taken from the manufacturing industry for two reasons. One is that the China's policies (e.g., the policy "Made in China 2025" and "internet plus manufacturing action") offer institutional support for manufacturing transformation of intelligent production. Another is that the China government has invested several billions into R&D of advanced technology (China Daily, 2016). Under the China's policies and the government's financial support, Chinese firms have gradually applied digital technologies in their production processes and some of them already have full implementation of PDI, offering a suitable context for obtaining sample firms and control firms and for exploring the long-time outcomes of PDI implementation. Therefore, the Chinese manufacturing is an appropriate research setting for this study.

4.2 Data collection

To examine the impact of PDI implementation on firm performance, we conducted an event study among the Chinese publicly listed firms over the past 13 years (i.e., 2006-2018). PDI refers to the application of digital, intelligent and networking technologies to conduct process innovation (Nambisan et al., 2017). Thus, such initiative should be commonly implemented in the industries with relevantly high levels of innovation (i.e. relevantly higher R&D expense). Based on the classification of industry in the Chinese Statistics Yearbook (2017) and the Chinese industry classification standards in 2017 and 2019 (i.e., GB/T 4754-2017), industries with relevantly high-level R&D intensity include medicine industry, electronic and device manufacturing, electric equipment manufacturing, machinery industry, metal and non-metal industry. Thus, this research targets mainly at these categories of industry.

For the process of selecting the experimental firm samples that implemented PDI, we referred to *Factiva* and *Wisenews* to collect the announcements of PDI implementation in publicly listed companies. *Factiva* is the most comprehensive database for company announcements and business news globally. *Wisenews*, which is the largest Chinese news database, has over 45,000 sources of news items from different kinds of media. It is usually used in studies concerning Chinese enterprises (e.g., Lam et al., 2016). More importantly, Chinese publicly listed companies have obligation to publicly disclose their detailed information of operations (e.g., PDI) to investors. To extract relevant announcements, firstly, we confirmed the key words by referring to the definition of PDI. It concerns with process digitalization initiative that applies digital technologies to data collection, data storage and analysis, automatic decision-making and production along the production process. Such initiative involves the implementation of digital technologies, for example, data collection technologies (e.g., internet of things, digital sensory and digital channel), data storage and analysis (e.g., cloud-based storage and cloud computing), automatic decision-making and production (e.g., additive manufacturing and robotic technologies). Secondly, we collected the announcements of digital manufacturing implementation from *Factiva* and *Wisenews* by using key words of process digitalization, intelligence and the above-mentioned technologies. The firms identified are shown in Table 1. Thirdly, we developed the initial dataset. We then carefully checked the announcements to assure that they were made by manufacturers (e.g., official website), rather than public opinion articles. We also deleted the repetitive firms with the announcements containing two or more searched key words. Next, in order to assure that no news related to PDI was missed, we conducted post-hoc search for announcements of all the listed publicly manufacturing companies in *Tengxun* financial stock using the key words. Finally, we shortlisted 168 firms as our experimental firms that implemented PDI, covering the time span from 2006 to 2018.

Following the prior literature (e.g., Lo et al., 2013, 2014), we developed a portfolio of comparable control firms and matched them with the experimental firms. The control firms were chosen based on three criteria. They are: industry, firm size and financial performance. Based on the studies of Barber and Lyon (1997) and Hendricks and Singhal (2008), we chose the firms with a total asset within 50-200% of sampled firms' total asset and with ROA within 90-110% of sampled firms' ROA as our matched control firms. We also checked to ensure that control firms and sample firms were included in the same publicly listed industry. Average matched control firms for sample firms are 2.23 firms.

The data of other variables (i.e., differentiation strategy, operational absorptive capacity, lean production, ROA, employees and total asset) were drawn from the China Stock Market and Accounting Research (*CSMAR*) database. The *CSMAR* database contains stock information and annual reports of all Chinese firms that have been traded publicly (Marquis and Qian, 2013). To state clearer, the data of absorptive capacity were collected from the corporate "R&D" innovation sub-database of *CSMAR*. The ones of lean level (i.e., inventory level) and ROA were collected from the financial indicator analysis sub-database of *CSMAR*. The data of employees and total asset were collected from the company profile sub-database and financial statement sub-database of *CSMAR*. Regarding control variables (e.g., industry types), we obtained archival data from the National Bureau of Statistics of China.

(------ Table 1 about here ------)

4.3 Measures

Process digitalization initiative: This variable was based on the manufacturers' list of public announcements on the implementation of PDI. The relevant keywords of PDI initiative are process digitization/intelligence and some key digital technologies applied in production process, i.e., production data collection technologies (e.g., internet of things, digital sensory and digital channel), data storage and analysis (e.g., cloud-based storage and cloud computing), automatic decision-making and production (e.g., additive manufacturing and robotic technologies), as shown in Table 1. The sources were *Factiva* and *WiseNews*.

Firm profitability: This research adopted return on assets (ROA) to reflect firm profitability, which is very commonly used to measure a firm's value or profit creation. It is measured as the net profit to total assets in the time span from year -2 to year +2 (Guthrie and Datta, 2008).

Differentiation strategy: It refers to the strategic orientation determining an organizational production routines that provide unique services or products to achieve customization (Banker et al., 2014). Firms adopting such strategy commonly need achieve high gross profit margin to afford the huge expense for R&D and advertisement of unique service or product (Selling and Stickney, 1989). This strategy also permits firms to achieve high margin by meeting customers' personalized requirements (Kim et al. 2004). As such, differentiation strategy is more inclined towards creating a high profit margin as the return of a company's superior products/service or differentiation operational process. Accordingly, this study employs Banker et al.'s (2011) measure of strategic positioning, that uses common accounting ratio (i.e., gross profit margin) to assess the differentiation strategy. It is calculated by gross operating profit over operating income in year +1.

Absorptive capacity: It is defined as an ability of a firm to leverage, acquire, assimilate and transform external information and knowledge into its operational process (Patel et al., 2012). Consistent with prior studies (Liu et al., 2014), we adopted R&D intensity to measure the absorptive capacity of each sample firm. R&D intensity can reflect the prior and current efforts of a firm in acquiring, assimilating and transforming its external resource into operating outcomes (Liu et al., 2014). We calculated R&D intensity of the sample firms as the R&D expenditure divided by the operating income from the adoption year (t-1) to the second year after adoption, i.e., year (t+1), then computed the median, which is the operational absorptive capacity.

Lean production: It concerns with the principles and tools that reduce excess inventory in the production process and enhance high outcome rates so as to achieve superior operational efficiency (Eroglu and Hofer, 2014; Iyer et al., 2019). Given that the level of inventory control is the basis of lean production, relevant literature suggests eliminating excess inventory from raw materials to finished product is a major indicator to measure the lean level (e.g., Iyer et al., 2019). In our study, the lean level relevant to production process associated with PDI is reflected by maximum inventory quantity hold in sampled manufacturing firms minus the inventory quantity hold of a firm, where the inventories include raw materials, package materials, semi-finished goods, finished goods and turnover materials.

Control variables: This research considers several control variables, namely prior performance, firm size, labor intensity and industry type. Prior performance influences the sequential period's changes of financial performance (Lo et al., 2014); therefore, we controlled ROA in year -2. Firm size may affect a firm's resources to perform digital innovation and influence the success of digital innovation strategy implementation (Hendricks and Singhal, 1997). Labor intensity is highly relevant to the automation of operational process (Hendricks and Singhal, 2008), which affects the implementation of digital innovation. Industry type exerts external pressure on firms' digital innovation adoption (Lo et al., 2013). Firm size is measured as the logarithm of a total asset (Lo et al., 2014). Labor intensity is determined by the ratio (i.e., the number of a firm's employees to its total assets) (Lo et al., 2013). Based on the China Statistical Yearbook (2017), six different types of manufacturing industries are defined. They are: electronic device manufacturing, electrical machinery manufacturing, equipment manufacturing, chemical manufacturing, metal manufacturing and others. Among digital innovation strategy adopters, the percentage of firms in electronic device manufacturing is the highest, accounting for 24.4%. The adopters in electrical machinery manufacturing and equipment manufacturing sectors are proportionately high, accounting for 15.5% and 20.8%, respectively.

4.4 Statistical models

4.4.1 Event study approach for longitudinal analysis

This study adopted a longitudinal event study approach to explore the causal relationship between PDI and firm profitability. Event study methodology has been developed and applied extensively in the literature of management. It mainly consists of short-term and long-term event study approaches. Short-term event study approach emphasizes the influence of an event within a relevant short time window (e.g., shorter than one year), which has been commonly applied to stock return change in a short-time window due to unexpected events (Klassen and McLaughlin, 1996; Albertini, 2013). Long-term event study approach expands the time window (i.e., consecutive several years) to examine the effects of an event through analyzing the experimental and control firm's abnormal performance change before and after such event occurs, finally achieving how an event affects the organizational performance over time. Long-term event study has always been applied to analyze the impacts of management practices (e.g., Sood and Tellis, 2009; Yu et al., 2021). Considering that PDI is an event that helps achieve long-term expectations of firm performance and that PDI is based on digital technology which needs certain time to become totally diffused in the organization, we employed the long-term event study approach to investigate the implementation effects of PDI. First, based on the firm announcement relevant to PDI, we defined the announcement time as year -1 (i.e., the year of PDI adoption), which is the first announced time of a firm to make the decision regarding digital transformation adoption. Since the average period of digital innovation from the adoption stage to the implementation stage is usually around one year (Ettlie and Vellenga, 1979; Triguero and Córcoles, 2013), we defined the event year (i.e., year 0) as the year when the firms are fully implementing digital production. We considered the base year of the event as year -2 (the year when the firms are free from the impact of PDI). As this study focuses on the long-term impact of PDI, abnormal performance changes from the start of announced adoption year (i.e., year -1) to the subsequent two years (i.e., year 0 and year 1) were investigated.

Next, we determined the abnormal performance in the sampled firms and compared with control firms. We calculated the abnormal performance using the following equation.

$$\mathrm{AP}_{(t+j)} = AS_{(t+j)} - EP_{(t+j)} \quad EP_{(t+j)} = \; AS_{(t+j-1)} + (CS_{K(t+j)} - CS_{K(t+j-1)}$$

where $\mathrm{AP}_{(t+j)}$ is the abnormal performance in $t+j$ year; AS is the actual performance of the sample firm in year $t+j$; $\mathrm{EP}_{(t+j)}$ is the expected performance of the sample firm in year $t+j$ and $\mathrm{CS}_{K(t+j)}$ is the actual performance of the matched control firm in year $t+j$. t is the fully implemented year of PDI; j is the ending year of comparison (j = -2, -1, 0, 1, 2). Subsequently, we conducted Wilcoxon sign-rank (WSR) test and sign test to examine abnormal performance change between sampled and controlled firms. Compared with parametric t-test, WSR test is less affected by outliers. However, for the purpose of ensuring robustness of the statistical results, we also conducted parametric t-test to determine the mean difference of abnormal changes.

4.4.2 Cross-sectional analysis of contextual factors

To test the moderating effects, this study employed a cross-sectional analysis with abnormal ROA as the dependent variable. Following prior studies (e.g., Hendricks and Singhal, 2008; Lo et al., 2014), we conducted the OLS regression to determine the moderating effects using the specific model as below.

$$AP_K = \beta_0 + \beta_1(PP_k) + \beta_2(Size_k) + \beta_3(LI_k) + \beta_4(IT_{ki}) + \beta_5(DS_k) + \beta_6(OAC_k) + \beta_7 \; (IS_k) + e_k$$

where k is the kth sampled firm; AP_K is the abnormal performance; PP_k is the prior performance; $Size_k$ is the sampled firm's size, LI_k is labor intensity; IT_{ki} is the types of industry; DS_k is the profit of margin generated from production, which refers to differentiation strategic climate; OAC_k is the firm's R&D intensity that concerns with absorptive capacity; IS_k refers to the inventory level, which is considered for lean production.

In this model, we controlled several firm-level and industry-level factors that might impact the outcome of digital innovation. These factors include the prior performance (i.e., the actual ROA) in year -2, firm size, labor intensity and different types of industries.

4.5. Results

4.5.1 Results from the event study analysis

Table 2 shows the results of sample firms' year-to-year abnormal changes analysis. As mentioned above, we collected 168 firms adopting the PDI and used all the available sample firms in each period to conduct WSR, rank and paired-T tests. There are two reasons for different sample sizes in the given time periods. One reason is that firms recently adopting PDI had not issued their financial data in year 0 or year 1, leading to different sample sizes. Another reason is that some firms adopting PDI were not become publicly listed companies in year -2. Thus, CSMAR database did not contain relevant financial information in year -2, yielding different sample sizes. The analysis is to exclude the impacts of other factors by using control firms and then compare the same company before and after adopting the practice. Studies using different samples at various time periods are common for event study analysis (e.g., Lo et al., 2014).

H1 predicts that the PDI has a positive impact on a firm's financial performance. As shown in Table 2, before the full implementation of PDI, the result for the periods (year -2 to year -1) is not significant, yet the abnormal change for the periods (year-1 to year 0) is statistically significant. These results indicate that sample firms have no significant abnormal change before the digital innovation decision-making (i.e., year -2 to year -1), while in the period from the digital innovation decision to PDI implementation (i.e., year -1 to year 0), the median change is -1.4%, which is significant at 1% level and only 37.7% of the sample firms achieved positive change. The results for the period (year 0 to year 1) are statistically significant. Specifically, the median change from (year 0 to year 1) is 3.7%, which is significant at 1% level and 74.8% of sampled firms achieve positive change. The mean of abnormal change in this period is 9.6%, which is significant at 5% level. Thus, the results demonstrate that firms fully implementing digital innovation can increase their profitability. The findings also reveal that PDI positively impacts the sample firms' long-term abnormal financial performance (i.e., ROA). H1 is therefore supported.

(------ Table 2 about here ------)

4.5.2 Results of the regression analysis

Table 3 displays the correlation matrix between the variables involving in the cross-sectional regression analysis. Table 4 concerns with the moderating effects on the effectiveness of PDI. The control model (i.e., Model 1) includes firm-level and industry-level control variables. Model 2 includes differentiation strategy and control variables. The statistical results of this model show that differentiation strategy positively moderates the impact of digital innovation on firm profitability ($\beta = 0.278$; $P < 0.05$), supporting H2. Such results expound that with the differentiation strategy, the implementation of PDI can achieve higher financial performance. In Model 3, the statistical results ($\beta = 0.200$; $P < 0.1$) reveal that absorptive capacity has a significant and positive impact on the relationship between PDI and firm profitability, demonstrating that at a high level of absorptive capacity, firms can attain higher profitability after implementing PDI, supporting H3. The statistical results of Model 4 ($\beta = -0.524$; $P < 0.05$) is significantly negative, suggesting that under a lean production environment, PDI takes a less effective role in increasing the profitability of a firm, not supporting H4. This finding is surprising and important. One possible explanation is that PDI could improve demand information visibility in the supply chain by using digital technologies to reduce operational cost (e.g., production cost and inventory cost) (Chen et al., 2015), thereby improving profitability. When companies employs lean practices, they standardize their operations process and in doing so, their operations costs can be reduced to a minimum level (Iyer et al., 2019). Thus, the implementation of PDI has a limited role in lowering the production and inventory costs of the companies that employ lean production. Another possible explanation is that process digitalization usually induces uncertainties in process and supply (Mellor et al., 2014), which necessitates slack resource to safeguard against the innovation variation. Companies with lean production almost have no slack resources that can be utilized to cope with the uncertainties and risks that are arisen when implementing PDI. Therefore, in such companies the effect of PDI implementation is limited. The above explanations support that PDI takes a less-effective role among the companies with lean production.

(------ Tables 3 and 4 about here ------)

4.5.3 Robustness test

To further examine the effects of PDI on firm profitability, this study collected the data from year 1 to year 2. For the period from year 1 to year 2, the median of abnormal change is 0.36%, which is significant at the 5% level and the mean is 3.7%, that is significant at the 1% level. In total, 55.6% of the sampled firms achieved positive performance. These results further confirm the robustness of the first hypothesis and indicate that PDI increases firms' profitability in subsequent two years of adopting the PDI practice.

This study examines the robustness of moderating effects of differentiation strategy, absorptive capacity and lean production. We replaced the measurement of lean production with inventory level. A high inventory level reflects a low level of lean production. Refer to the method outlined by Liu et al. (2014), we firstly sorted each of the three variables and classified them into ten percentile groups from low to high level. Next, we followed the sequence from low to high level to assign a score from 1 to 10 to the groups of each variable. Third, we computed the total scores of three variables and classified the sample firms into three groups. The results in Table 5 indicate that under high-level differentiation, capacity and inventory, the mean and median of abnormal ROA change is the highest (Mean = 0.081, Median = 0.065). Finally, we conducted the Mann-Whitney test and independent T test to compare the ROA abnormal change in different groups. The results in Table 5 reveal that the mean difference of abnormal ROA in the high-medium group (t value = 1.889) and the high-low group (t value = 2.247) are significant and the median difference statistical results of abnormal ROA in these two compared groups are also significant (z value = 2.408 for the high-medium group; z value = 3.101 for the high-low group), demonstrating the robustness of the results concerning the moderating effects.

(------ Table 5 about here ------)

5. Discussion and Conclusion

5.1 Discussion

Process digitalization is being increasingly adopted in firms to achieve business goals and organizational competitive advantage. Proponents of digital manufacturing proponents generally perceive that PDI induces a dramatic change in solving their operational issues and yields significant improvement in operational processes (Nylén and Holmström, 2015). But the implementation of digital manufacturing often forces firms to change their existing operational environments, including product and service portfolio and the ways in which operational activities are conducted. This may cause potential innovation risks to organizations, affecting the firm's performance. The actual organizational impact of digital transformation at the firm level is under-explored (Chen et al., 2015). Thus, this study empirically examines the actual impact of PDI on firm profitability through a longitudinal effect analysis on digital implementation. Viewed from the core dimensions of dynamic capability development (i.e., purpose, process and people), we further investigate how strategic orientation, absorptive capacity and lean production facilitate organizational adaption to the PDI implementation through developing dynamic capability. Such adaption is definitely critical to the diffusion of advanced technological innovation to organizational operations.

Our findings demonstrate that PDI improves firm profitability. In the preparation period (i.e., from the adoption of digital technology to the full implementation), enterprises have a significant negative change on ROA. This is due to the cost related to firms' investment in digital technologies and platform establishment. Yet, for the following two years after the adoption, i.e., the two years of full implementation, enterprises have a significant positive change of ROA. After the adoption, PDI can help firms accurately predict customers' requirement and preference through the obtained real-time customer data. The manufacturing process of PDI is close to customer end; in turn, this reduces production cost and transportation cost. Digital innovation strategy therefore helps achieve a positive change on ROA in the following periods after the adoption.

The differentiation strategy is a facilitator for successful implementation of PDI by developing dynamic capability. We adopted the gross profit margin as the proxy to reflect the differentiation strategy. Firms with high gross profit margin offer strategic motivation for new products development. They are therefore likely to build close relationship with suppliers and customers for innovation capability development. This is beneficial to companies when implementing PDI, thereby enhancing the impact of PDI implementation. Our findings also demonstrate that absorptive capacity influences the effectiveness of PDI. Absorptive capacity can increase a firm's flexibility in response to technological change, routine change and process change, thereby developing the dynamic operational capability for the firm. Such capability aids the firm to acquire and assimilate valuable information about process innovation as well as reconfigure and realign its external and internal resources in order to facilitate the implementation of PDI.

The results indicate that lean production mechanism weakens the effectiveness of PDI on profitability. To implement PDI, companies may make use of digital technologies to improve the demand information visibility, thereby reducing operational costs (e.g., inventory cost). Companies that employs lean production can usually achieve the operational cost at a minimum. Under such a situation, the role of PDI to lower the operational cost of companies becomes unclear, leading to limited firm profitability improvement. In addition, PDI implementation needs slack resource to cope with uncertainties and threats in process digitalization. Whereas for firms with lean production, there is often no excess inventory of raw materials and finished goods that can safeguard against the potential risk of digital innovation; as such, the effectiveness of PDI implementation becomes limited.

5.2 Theoretical implication

This research has three main theoretical implications. First, this study enriches the literature of digital technologies and operations management by exploring a critical question concerning the actual impact of PDI on improving firm profitability. The current literature usually highlights that PDI is an imperative to service or product customization (Fink et al. 2020) and indicates that PDI can reduce product development time and cost and can be used to replace the traditional manufacturing with model-based production (Atzeni and Salmi, 2012). However, the actual impact of PDI is indeed unclear. This research fills this gap in whether PDI influences firm profitability and how firms can successfully implement digital manufacturing using advanced technologies.

Next, this research links dynamic capability with digitalization transformation to analyze how strategic orientation, absorptive capacity and lean production cope with the process change caused by the implementation of PDI. Prior studies emphasize the importance of dynamic capability in digital manufacturing (Heinen and Hoberg 2019; Roscoe et al., 2019), whereas this study explores how to develop dynamic capability to support for PDI by considering the interplay among PDI, strategic orientation, absorptive capacity and lean production through the lens of dynamic capability.

Last, this study uses the objective measures to assess the strategic orientation, absorptive capacity and lean production. Many studies examine the effects of strategy related to capability and process using survey and case study methods (e.g., Lu and Ramamurthy, 2011; Danneels, 2011). This study uses an accounting indicator, gross profit margin, as the proxy for differentiation strategy and firm operational indicators, for R&D intensity and inventory level, as the proxy for absorptive capacity and for the lean production, respectively. The use of these accounting and operational indicators reduces cognitive bias induced from subjective data, enhancing the rigor of the study.

5.3 Practical implication

This study offers three practical implications. First, executive officers should realize that digital manufacturing is a new transformation approach for production to generate profit. In the early stage (around one year after the adoption of digital innovation to the full implementation), firms need to invest new digital technologies and platform establishment, resulting in a lower level of ROA. In the subsequent two years after the adoption, process innovation can generate profit to firms. It is therefore recommended that in the early stage after the adoption, when firms may face the challenge of ROA reduction, they should continue to develop their digital platforms and seek ways to diffuse advanced technologies into their operations processes. In a longer run, this helps them to reap the benefit from the PDI implementation.

Second, operations managers are suggested to realize that differentiation strategy is a key factor to develop the dynamic operational capability for PDI by providing flexible operational process. This can ensure that PDI can be pushed forward smoothly in their companies. People knowledge capability is also an important facilitator to develop firms' adaptive capability to attain successful implementation of PDI. Firms are recommended to invest more on R&D. In doing so, they would find that digital technologies are more effective to generate higher gross profit margin. Furthermore, firms are suggested to pay more attention to their knowledge acquisition and assimilation from external resources, which can facilitate the ease of learning about digital innovation and the ways to implement it. In addition, PDI has a substitution role in the effects of lean production. Firms using classical lean methodologies usually reduce waste by standardizing their process and continuous improvement, whereas PDI use the advanced digital technology to conduct auto-production. Thus, lean companies are not able to make further significant improvements with classical lean methodologies. Instead, PDI provides a new toolset for firms to improve performance. Also, firms without slack resource are recommended not to expect for any safeguard against potential risks of digital innovation.

Last, the findings offer useful guidelines to policy-makers and governments, especially those from countries where PDI is at a “beginner” level, for example China. The governments are suggested to give priority to support those firms incorporated with differentiation strategic climate. In doing so, these firms can move the pace of digital process innovation faster and smoother. Policy-makers should also encourage firms to enhance R&D intensity and balance lean production and innovation. This enables firms to be readier for digital transformation.

5.4 Limitation

This study has several limitations and recommendations for future research. One limitation is that the study samples include only Chinese publicly listed firms that announced the implementation of digital innovation strategy and had financial data. The effects of digital innovation on firm performance might vary in different countries due to various cultures and institutional environments (Kull and Wacker, 2010; Lo et al., 2014). Thus, further research may be conducted by collecting samples from other countries for comparing the effects difference of PDI. Another limitation is that this study adopts single indicators to measure absorptive capacity and lean production. Future studies should adopt multiple proxies to measure these variables from different perspectives. For example, lean production can be measured by integrating different indicators at the inventory level, the manpower level and the waste level. Finally, this study focuses on the key organizational factors (i.e., internal factors). Since external factors (e.g., institutional forces) also take an important role in the implementation of digital innovation strategy, future studies may explore how external factors (e.g., institutional forces) impact the effectiveness of digital innovation implementation.

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Figure and Tables

Figure 1 The Conceptual Model

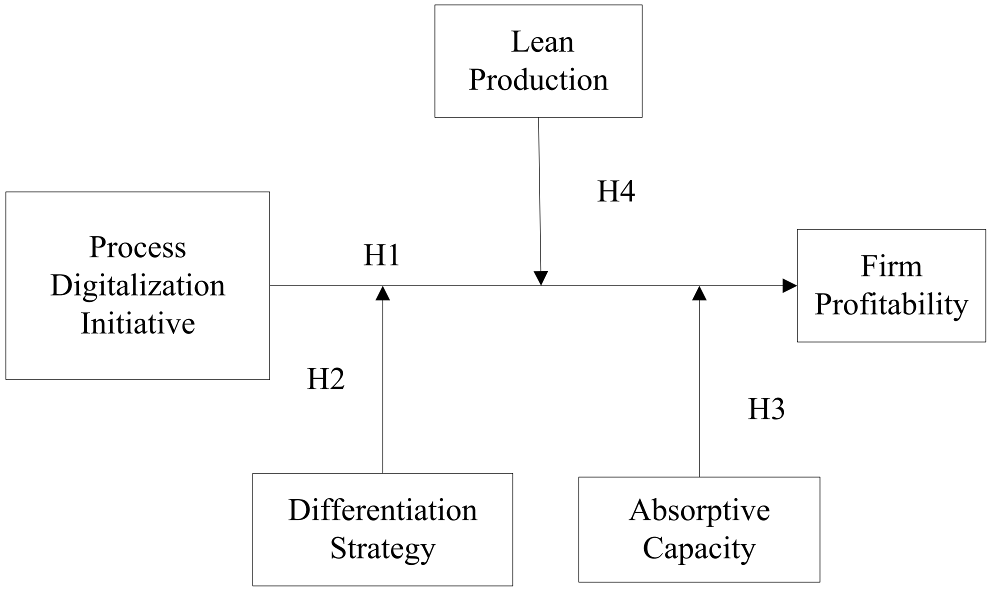

Table 1 The Number of Firms Collected by Different Key Words

Key words	Number of firms	Example of announcement
Production digitization / intelligence	85	"Jiangsu Hengshun Vinegar-Industry Co., Ltd (Stock No. 600305) adopts advanced technologies such as big data analysis, Internet of things technology, production information control system (MES), industrial robot and visual recognition. It integrates automation, digitalization and intelligence, and comprehensively improves the intelligent level of the production process in the condiment industry." (Announcement in year 2015)
Internet of things / digital sensory	20	"Zoomlion Heavy Technology Co., Ltd (Stock No. 000157) The Intelligent Cloud Service Platform Based on the Internet of things has been built through Internet of things technology, Beidou navigation technology, cloud computing, big data analysis... " (Announcement in year 2015)
Cloud-storage and computing / cloud platform	34	"Lepu (Beijing) Medical Devices Co., Ltd. (Stock Code: 300003) applies Internet technology and cloud computing to develop NT proBNP test equipment that can be used in families with mobile phones." (Announcement in year 2013)
Additive manufacturing	21	"Antaike Technology Co., Ltd. (Stock Code. 00969） applies additive manufacturing inpowder material engineering filed." (Announcement in year 2013)
Robotic technology	18	"Skyworth Digital (Skyworth Group Co., Ltd.) (Stock Code 000810) SKYWORTH uses 'robot strategy' to open the door of intelligent manufacturing." (Announcement in year 2012)

Table 2 Results of Sample Firms' Year-to-year Abnormal Performance

	Year -2 to Year -1				Year -1 to Year 0				Year 0 to Year 1			
	N	Median	Percentage	Mean	N	Median	Percentage	Mean	N	Median	Percentage	Mean
ROA	161	0.0011	52.8%	0.0211	136	-.0140	37.7%	-.0759	103	0.0370	74.8%	0.0961
Statistic		.259	0.712	-1.054		-2.679**	-2.582*	1.294		4.848**	4.927**	1.998*

Noted: Z statistics for Wilcoxon signed test (median), sign test (percentage) and T-statistics for test (mean)

Percentage indicates the percentage of firms achieving positive abnormal changes in ROA

+ Note a statistically significant difference at 0.1 level (P<0.1)

* Note a statistically significant difference at 0.05 level (P<0.05)

** Note a statistically significant difference at 0.01 level (P<0.01)

Table 3 The Correlation Matrix of Variables in the Regression Analysis

Variables	Mean	S.D.	AR	PP	LI	EI	M	E2	C	M	O	DS	AC
Abnormal ROA (AR)	0.04	0.10											
Prior performance (PP)	0.06	0.04	.003										
Labor intensity (LI)	7.1E-7	6.4E-7	.039	0.093									
Electronic industry (E1)	.27	.44	-.060	-.023	-.008								
Machinery (M)	.14	.35	-.022	.032	-.050	-.170*							
Equipment (E2)	.21	.41	.017	-.024	-.114	-.283*	-.213**						
Chemical (C)	.07	.25	-.025	.012	-.079	-.160*	-.108	-.138					
Metal (M)	.08	.28	-.017	-.097	-.106	-.182*	-.062	-.157*	-.080				
Others (O)	.22	.42	.030	.108	.237**	-.321**	-.217**	-.278*	-.141	-.160*			
Differentiation strategy (DS)	.31	.16	.229*	.422**	-.012	-.011	-.105	-.094	.155*	-.240**	.192*	-.104	
Absorptive capacity (AC)	.03	.02	.208*	.184	.198*	.291**	.054	-.192*	-.135	-.109	-.061	-.164	.204*
Lean production (Lp)	1.8E+11	2.4E+10	-.112	.091	.167	.089	-.009	.102	-.151	.048	-.204*	.123	.201*

* Note a statistically significant difference at 0.05 level (P<0.05)

** Note a statistically significant difference at 0.01 level (P<0.01)

Table 4 Results of the Moderating Effects from Regression Analysis for the Variables in Year +1

Dependent Variable - Abnormal ROA				
	Model 1 (Control model)	Model 2	Model 3	Model 4
Prior financial performance	.107(.991)	-.007(-.059)	-.034(-.290)	-.005(-.039)
Firm size	.067 (.601)	.112(1.005)	.133 (1.205)	-.323(-1.351)
Labor intensity	-.019(-.165)	.045(.390)	.012(.105)	.039(.347)
Industry type				
Electronic Industry	-.337(-1.518)	-.258(-1.175)	-.276(-1.270)	-.300(-1.409)
Electricity machinery industry	-.136(-.765)	-.039(-.220)	-.034(-.195)	-.066(-.378)
Equipment industry	-.199(-.881)	-.08(-.353)	-.037(-.164)	-.050(-.226)
Medicine industry	-.120(-.942)	-.129(-1.030)	-.093(-.746)	-.199(-1.510)
Metal industry	-.042(-.273)	.040(.255)	.064(.417)	.064(.426)
Others	-.125(-.583)	-.079(-.375)	-.043(-.204)	-.080(-.391)
Differentiation strategy		.278**(2.234)	.255* (2.062)	.283** (2.322)
Operational absorptive capacity			.200* (1.755)	.200* (1.790)
Lean production				-.524**(-2.144)
R square	0.064	0.117	0.149	0.195

The coefficient is standardized coefficient.

* Note a statistically significant difference at 0.1 level (P<0.1)

** Note a statistically significant difference at 0.05 level (P<0.05)

Table 5 The Differences of Abnormal ROA in Low and High Absorptive Capacity, Low and High Differentiation Strategic Climate and Low and High Inventory Level Fit Groups at Year +1

	High Fit Group	Medium Fit Group	Low Fit Group
Firm No.	36	36	29
Mean	0.081	0.041	0.023
Median	0.065	0.036	0.017
	High-Medium group	High-Low group	Medium-Low group
Mean comparison	1.888*	2.247**	0.735
Median comparison	2.408**	3.101***	1.256

Noted: the value is Z value in Mann-Whitney for median comparison and t value in independent sample t-test for mean comparisons,

* Note a statistically significant difference at 0.1 level (P<0.1)

** Note a statistically significant difference at 0.05 level (P<0.05)

*** Note a statistically significant difference at 0.01 level (P<0.01)